EXPLORING ECONOMIC INEQUALITY AND ITS IMPACT ON CAREER CHOICES

Presented by: Group 6

INSPIRATION BEHIND THE PROJECT

- Societal Stereotypes:
  - Technical roles are often linked to less affluent students.
  - Humanities and non-technical majors are associated with affluent backgrounds.
- Research Question:
  - Is there evidence to support this stereotype?
- Purpose:
  - Use university-level student data to test this stereotype.

OBJECTIVE OF THE STUDY

- Impact of Economic Backgrounds:
  - Investigate how financial circumstances shape career choices.
- Focus:
  - Analyze preferences for technical vs. non-technical professions.
- Link to Career Outcomes:
  - Understand the effects of economic barriers on academic and career decisions.

TESTING HYPOTHESIS AND ANTICIPATED IMPACT

- Hypothesis:
  - Economic background significantly influences students' choice of technical or non-technical majors.
- Expectation:
  - Financial changes correlate with shifts in major selection and career outcomes.

POTENTIAL IMPACT OF FINDINGS

- Insights for Universities & Policymakers:
  - Inform strategies to mitigate economic disparities.
- Promote Equal Opportunities:
  - Address barriers to education based on financial background.
- Enhance Workforce Diversity:
  - Help reduce economic gaps in education and employment.

DATASET OVERVIEW

- Sample Study: A sample, not a census, due to challenges in assessing all university students in Pakistan.
- Target Population: Undergraduate students from five top universities (e.g., LUMS, FAST NUCES, NUST, and two others).
- Sampling Method: Convenience sampling via an online survey distributed through Google Forms and student platforms.

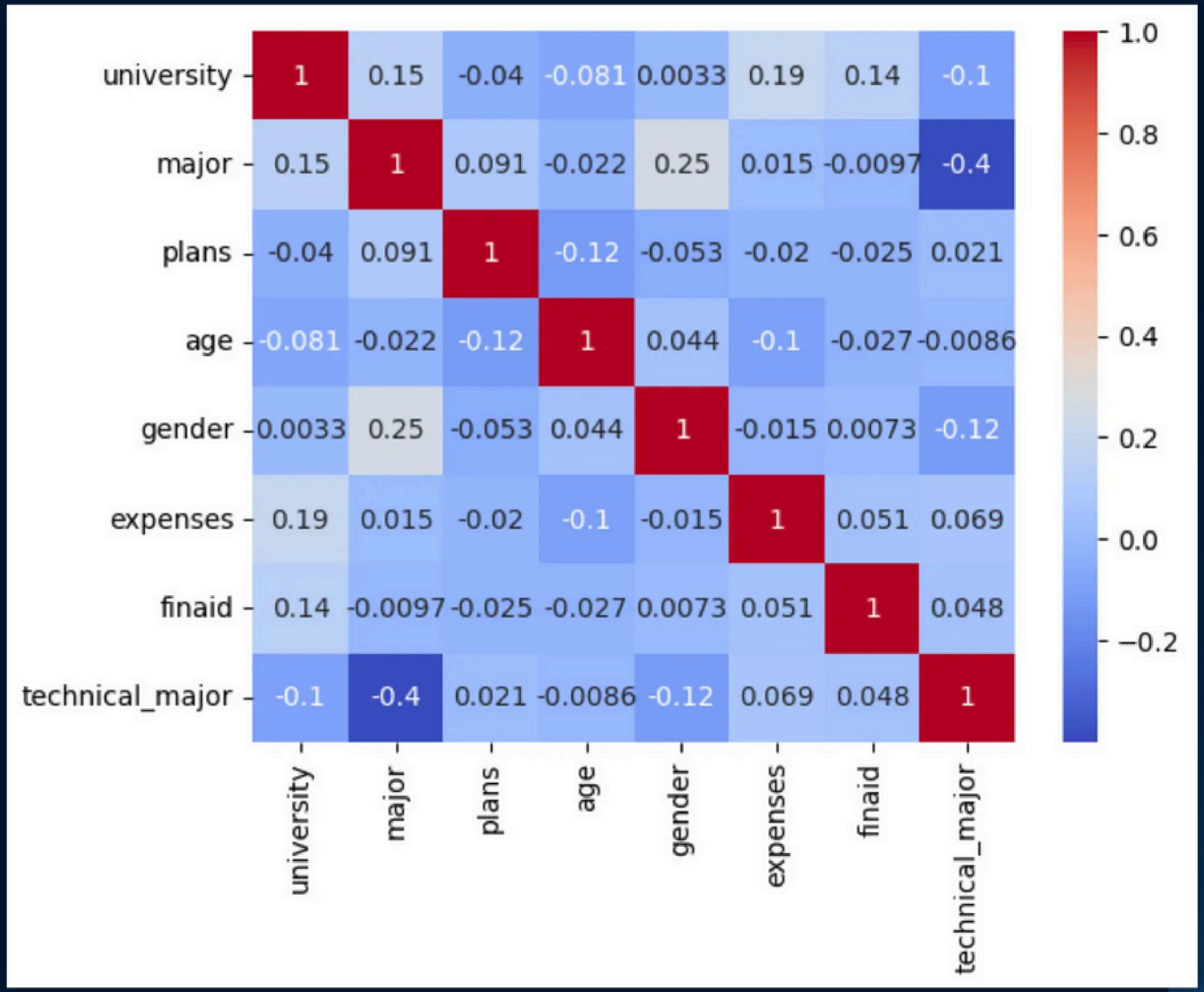
KEY VARIABLES

- Income Levels: Household income brackets.
- Academic Major: Technical vs. Non-technical (binary: 1 = technical, 0 = non-technical).
- Career Plans: Industry, academia, or self-employment.
- Demographics: Gender, age bracket, and university affiliation.

EXPLORATORY DATA ANALYSIS

Understanding the Dataset

- The correlation matrix identified correlations between variables and the likelihood of choosing a technical major
- Key insight: The correlation between family expenses and technicality of the major is weak (0.069).
- Gender and major technicality exhibit stronger trends, warranting further exploration.



EXPLORATORY DATA ANALYSIS

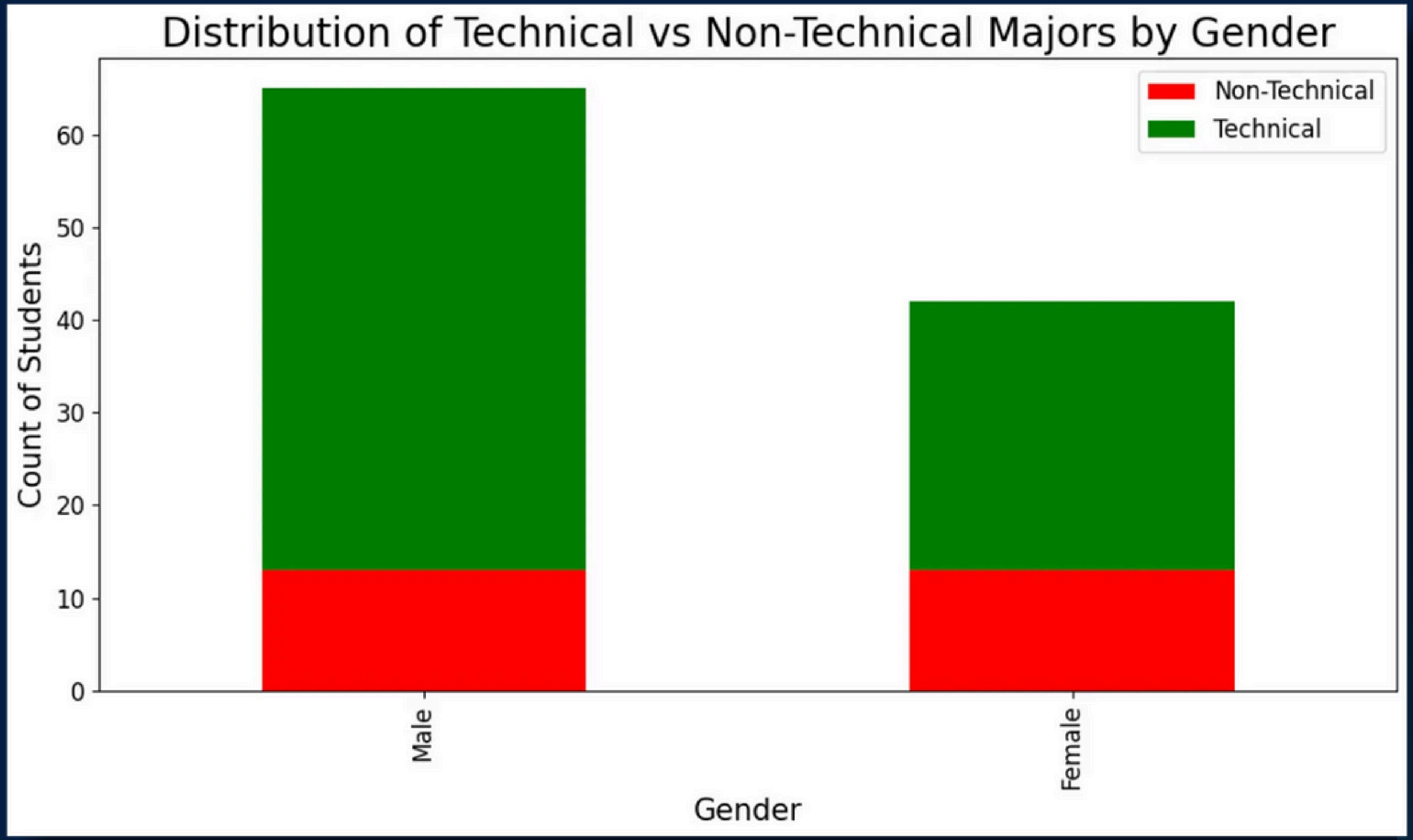
Gender Influence on Major Selection

Observation

- Males predominantly choose technical majors.
- Females also show a preference for technical majors, though slightly lower in proportion.

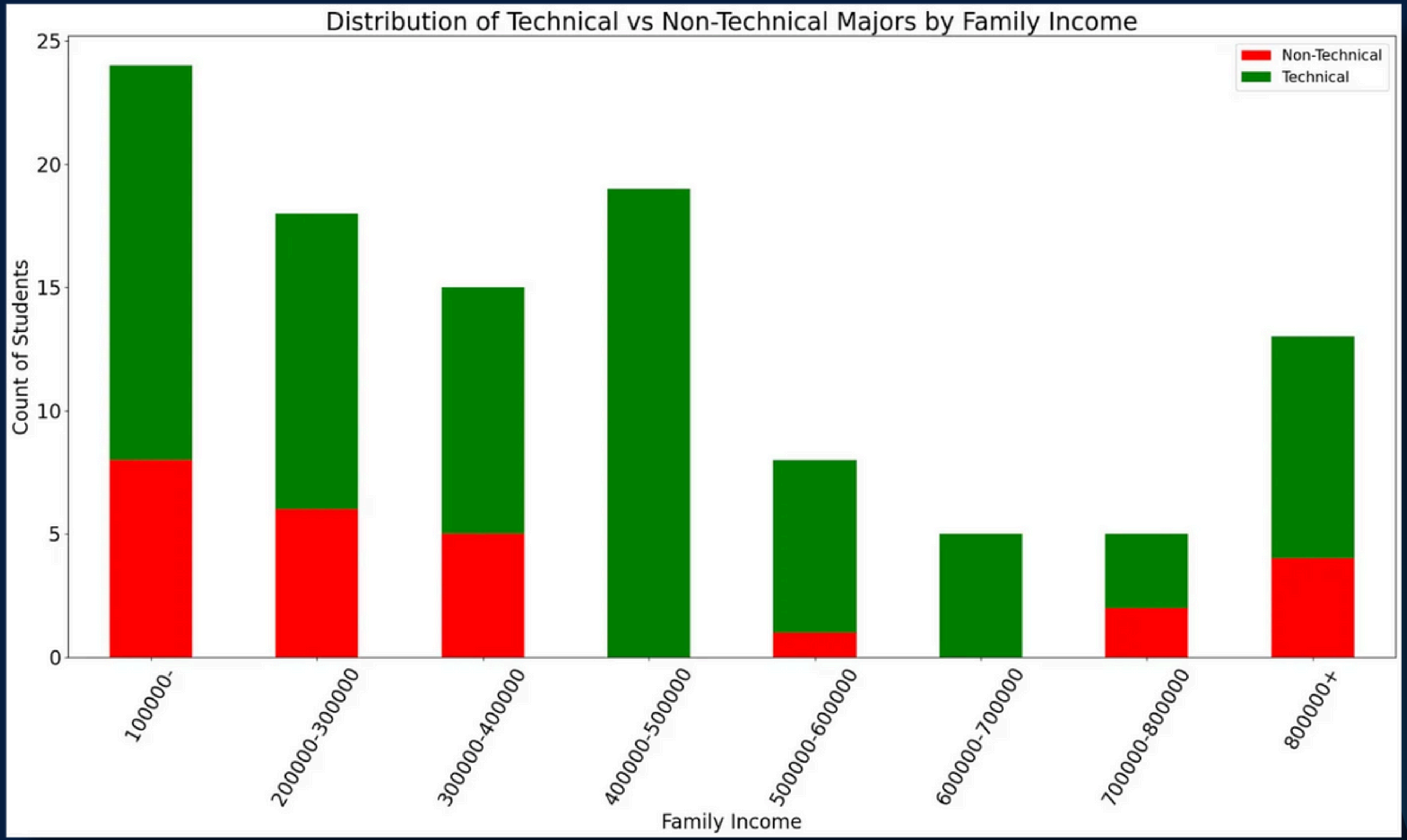
Implication

- Suggests a general trend favoring technical fields across genders, but males dominate.



EXPLORATORY DATA ANALYSIS

Family Income vs. Technical Major Preference



Key Insights

- Preference for technical majors peaks in families with monthly expenses of 400,000–700,000 PKR.
- Across all income brackets, technical majors dominate.

ML MODEL

LOGISTIC REGRESSION

WHY DID WE CHOOSE IT?

- Suitable for binary classification problems.
- Provides interpretable output in terms of probabilities.
- Handles linearly separable data efficiently.

MODEL DESCRIPTION

- Predicts a binary outcome (e.g., "Technical = 1" or "Non-Technical = 0").
- Fits a logistic function to map input features to probabilities.

FEATURES AND PREPROCESSING

- **Dropped Features**: Timestamp (not relevant for prediction).
- **Encoded Features**: Categorical variables were one-hot encoded.
- **Left as-is**: Age (numerical, does not need encoding).

MODEL TRAINING

- Data split into training (80%) and test (20%) sets.
- Logistic regression trained with a maximum of 1000 iterations.

METRICS

90.9% ACCURACY

93% PRECISION

7	1
0	3

CONFUSION MATRIX

91% RECALL

INSIGHTS

- Model predicts the majority class (1 = "Technical") very well.
- High precision and recall for the "Technical" class indicate strong model performance.
- Misclassification in minority class (Non-Technical) indicates room for improvement in balancing.

KEY TAKEAWAYS

- The model is effective for this dataset but might benefit from more samples in the minority class (Non-Technical).
- Suitable for decision-making in classifying technical skills.

POSSIBLE AREAS OF IMPROVEMENT

- Collect data from a larger and more diverse sample to increase the generalizability of the findings

- Replace convenience sampling with stratified or random sampling to reduce selection bias.

- Create an ensemble of Machine Learning classifiers like decision trees or random forests to see if they improve predictive performance.

THANK YOU

https://drive.google.com/file/d/162hQ2b_9R6oxnoSzL5WeiIuLsoy0iHyZ/view?usp=sharing